

Semantic Parsing and its Applications in Code Generation

Mentors: Navin Goyal and Monojit Choudhury

Problem Overview



Problem Overview: Natural Language Interfaces



- Programmer-oriented use-case
- Search for code by functionality
- Generate code via NL



Problem Overview: Robot Navigation

- Communicating with robots using NL
- Conversion of instruction to DSL
- Context-dependent instructions

Previous instruction:

Go to the tree on the right **Previous interpretation:** $\lambda_{a.move(a)} \wedge \lambda_{x.tree(x)} \wedge right$

of (x, rock) \wedge to(a, x)







Source: https://github.com/allenai/acl2018-semantic-parsing-tutorial/blob/master/slides/context_dependent_parsing.pdf

Traditional vs Neural Parsing

Traditional

- Manual grammar+lexicon creation
- Deterministic or probabilistic parsing
- Highly accurate parsing
- Restricted domain

Neural

- Parsing as sequence-to-sequence generation problem
- Data-driven
- Robust, scalable
- Margin of error

Problem Overview

Why is it difficult? Precision vs. robustness



Source: https://web.stanford.edu/class/cs224u/materials/cs224u-2016-intro-semparse.pdf

Objectives and Progress

Model Objectives

- NL2Regex
- Study, implement different parsing techniques
- Beat the state-of-the-art model

Data Objectives

- Study existing datasets
- Identify failure points in datasets
- Analyze efficiency of data collection techniques

Model Objectives

NL2Regex

NL-RX dataset (Locascio et.al 2016)

- 10,000 pairs of NL descriptions and regex
- Grammar-based generation + paraphrasing



Lines start with number and contains the string "dog"

Paraphrase

Lines which start with a number and contain the string "dog" in it.

Semantic Parsing Models: Current SOTA

• Seq2Seq w/ attention

Advantages:

- Quick to train
- Robust to variation

Disadvantages:

- No structural integrity in logical form
- Unable to handle large nesting in logical forms



Semantic Parsing Models: Coarse2Fine

Two stages of encoding-decoding:

- 1. NL is encoded, sketch is decoded
- 2. Sketch is encoded, logical form is decoded

Advantages:

- Structure is encoded, guides decoding throughout
- Work of encoding-decoding is divided

Disadvantages:

 May still result in syntax errors



Source: Coarse-to-Fine Decoding for Neural Semantic Parsing (Dong and Lapata 2018)

Semantic Parsing Models: Seq2Tree

• Tree decoder instead of sequence decoder

Advantages:

• Leverages tree/nested nature of code during decoding

Disadvantages:

 Structure is not encoded explicitly, does not guide the decoding



Semantic Parsing Models: Abstract Syntax Networks

• Recursive calls of decoding modules

Advantages:

- Leverages recursive nature of general programs
- Output is always syntactically correct

Disadvantages:

- Lack of effective encoding of NL
- Not generalizable to all semantic parsing problems



Semantic Parsing Models: Multi-Task Learning Models

- Joint training of multiple tasks
- Common loss function

Advantages:

- Learns more informed representation of NL
- Encoding of NL is more advanced

Task 1 Task 2 Common Multi-task Loss Model Function Task 3 Task 4

Disadvantages:

• No structural integrity of decoding

Model	Exact Matching Accuracy	DFA-Equals Accuracy
Baseline (Seq2Seq + Copy)	38.96%	55.24%
Current SOTA	38.6%	58.2%
Coarse2Fine	42.52%	59.68%
Multi-task Network (MQAN)	44.96%	61.92%

Error Analysis

1. Incorrect Paraphrasing

Synth: lines having either a lower-case letter, the string "dog", or a number before a capital letter Paraphrase: lines containing a lower - case letter and the word dog, followed by a number, then a capital letter

Correct regex: (([a-z]) | (dog) | ([0-9])) .* ([A-Z]) .* Predicted regex: (([a-z]) & (dog)) .* ([0-9] .* [A-Z] .*) .*

2. Transferred ambiguity

Synth: lines with the string "dog" before the string "truck" or the string "ring", 6 or more times Paraphrase: lines with string "dog" before string "truck" or string "ring", 6 or more times

Correct regex: (((dog) .* (truck) .*) | (ring)) {6,} Predicted regex: ((dog) .* (truck) .*) | ((ring) {6,})

3. Large syntactic variation

```
Synth: lines containing a character and a lower-case letter
Paraphrase: a character and a lower cased letter is required of lines
```

```
Correct regex: .* ( . ) & ( [a-z] ) .*
Predicted regex: ( ( . ) & ( [a-z] ) ) .* ( [0-9] ) .*
```

Data Objectives

Existing Datasets: NL2Program Datasets

1. Hearthstone



class DireWolfAlpha(MinionCard): def __init__ (self): super().__init__ ("Dire Wolf Alpha", 2, CHARACTER_CLASS.ALL, CARD_RARITY.COMMON, minion_type=MINION_TYPE.BEAST) def create_minion(self, player): return Minion(2, 2, auras=[Aura(ChangeAttack(1), MinionSelector(Adjacent()))])

2. NL2Bash

display the 5 largest files in the current directory and its sub-directories find . -type f | sort -nk 5,5 | tail -5 du -a . | sort -rh | head -n5

3. Django

join app_config.path and string 'locale' into a file _____ path, substitute it for localedir. localedir = os.path.join(
 app_config.path, 'locale')

4. CoNaLa

How can I send a signal from a python program?

> os.kill(os.getpid(), signal.SIGUSR1)

Name	Domain	NL
ATIS	Airline Booking	What flights from any city land at airport_code0 ?
GeoQuery	US Geography	could you tell me what is the highest point in the state of Utah ?
WikiSQL	Various (e.g. Movies, Sports, History)	Srdjan Dragojevic worked on a film which earned what nomination?
Spider	Various (e.g. Games, Class schedules, U.S. government)	For every student who is registered for some course, how many courses are they registered for?

Navi



Instructions:

Place your back against the wall of the T intersection

Turn left

Go forward along the pink flowered carpet hall two segments to the intersection with the brick hall

SCONE

Empty out the leftmost beaker of purple chemical	
Then, add the contents of the first beaker to the second	
Mix it	
Then, drain 1 unit from it	
Same for 1 more unit	

Factors to determine data quality

Natural Language

- NL Variation
 - Lexical
 - Phrasal
 - Syntactic
- **NL Quality**: Grammatical errors, mispellings,etc.
- Level of Anaphora
- Domain span

Logical Forms

- LF Variation: Coverage
- LF Complexity: Nesting (depth)
- LF Consistency: Dense distribution of LFs
- **LF Quality**: Syntactic and semantic accuracy

Some Qualitative Observations

Dataset	NL variatio n	NL Quality	Level of Anaphora	LF variation	LF complexity	LF consistency	LF Quality	Domain Span
NL2Regex	×	×	×	×	×	\checkmark	×	×
Django	×	V	×	\checkmark	V	V	\checkmark	\checkmark
WikiSQL	\checkmark	\checkmark	×	×	×	\checkmark	\checkmark	\checkmark
Spider	\checkmark	\checkmark	×	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Scone	×	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	×

Quantitative Analysis Metrics

Natural Language

- 1. Size of vocabulary
- 2. Av. length of datapoint
- 3. Level of anaphora
- 4. N-gram variation
- 5. Zipf distribution of words

Logical Forms

- 1. Av. number of nodes in AST (Gen. purpose programs only)
- 2. Av. number of operators/operands
- 3. "N-gram variation"

Some Quantitative Results: Level of Anaphora



Some Quantitative Results: Zipf distribution of words



Slope of plot of log(freq. of word) vs. log(rank of word)

The **closer to 1**, the better the frequency distribution of words

Inferences:

- 1. Good datasets have <u>high</u> Zipf slope (Spider, Conala, Hearthstone)
- 2. NL2Regex has <u>poor</u> <u>distribution</u>
- Seq+Context-dep datasets <u>don't focus</u> on accurate distribution



Data Cleaning

• How to *abstract away* the task and logical form complexity from NL variation?

- Three step cleaning:
 - Replace named entities with <NE>
 - Replace words which are <u>not common</u> <u>words</u> and have <u>frequency > 3</u> with
 <KW>
 - Replace those with <u>frequency < 3</u> with
 <NE>

Django NL query:

call the function _create_cache with argument alias

NL2Regex NL query:

lines with the string 'dog' at least 2 times

Some Quantitative Results: N-gram NL variation

3-gram NL variation:

- 1. Sort unique 3-grams in descending order of frequency
- 2. Take top 20% of this list, and find % of datapoints which contain these 3-grams
- 3. The <u>higher the %</u>, the <u>less variation</u> there is.

Inferences:

- Django dataset and NL2Regex datasets <u>comparable</u>.
- 2. Spider <u>maintains</u> variation level, whereas variation of WikiSQL is <u>lesser</u> <u>than expected</u>



Some Quantitative Results: 3-gram NL variation vs. 3-gram Code Variation



Data Collection Analysis

• Devised a generalized set of methods used for data collection.



NL-J	ohase Collection
Inpu	ts:-
1.	NL description
2.	LF description
3.	World description
Proc	cess:-
1.	Generate NI
2.	Extract
3.	Paraphrase

Data Collection Analysis

<u>LF-pha</u>	se Classification	Process				
		Scrape		Generative Model		Manual
	Web/Internet	CodeNN, <u>Conala</u> ,Geoquery, <u>Hearthstone</u> ,IFTTT,NL2Bash		WebQuestions		
Input	Grammar+Lexicon	Invalid	<u>NL2Regex</u> ,Overnight, <u>WikiSQL</u>			
	World State Invalid			<u>SCONE</u>		ATIS, <u>Spider</u>
NL-phase Classification		Process				
		Generate	Extract		Paraphrase	
	NL description	WebQuestions	CodeNN, <u>Conala</u> ,Geoquery, <u>Hearthstone</u> ,NL2Bash,IFTTT		<u>NL2Regex,WikiSQL,</u> Overnight	
Input	LF description		Conala, NL2Bash		Invalid	
			Invalid			

Future Work

- 1. Collect small regex datasets with different methods
- 2. Analyze the data and determine efficient data collection methods and strategies.
- 3. Measure code complexity with advanced measures such as :
 - a. Halstead complexity
 - b. Cyclometric complexity

